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# Conflict Prediction Through Geo-Spatial Interpolation of Radicalization in Syrian Social Media

**TRADOC Analysis Center**
**700 Dyer Road**
**Monterey, CA 93943-0692**

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## Authors

**MAJ Adam Haupt**
**Dr. Camber Warren**

**PREPARED BY:**

**ADAM HAUPT**
**MAJ, US Army**
**TRAC-MTRY**

**APPROVED BY:**

**CHRISTOPHER M. SMITH**
**LTC, US Army**
**Director, TRAC-MTRY**

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# ABSTRACT

While there is widespread agreement amongst scholars and practitioners that processes of popular radicalization frequently underlie the generation of insurgent violence, an absence of high-resolution data has prevented existing work from directly modeling this relationship. A spatio-temporal map of extremist discourse would allow planners to monitor the emergence of social radicalization prior to the eruption of large-scale violence. Moreover, by utilizing newly developed statistical techniques for geo-spatial causal inference, such data can provide a basis for generating systematic predictions of the location and timing of future episodes of collective violence. As an initial demonstration of the value of this approach, this project focuses on estimating spatial-temporal quantities from the content of Twitter messages originating within Syria. Geo-spatial interpolations of these quantities will then be used to generate predictions of the locations of violent events within Syria.

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# LIST OF ACRONYMS AND ABBREVIATIONS

| | |
|---|---|
| CPU | Central Processing Unit |
| GPU | Graphics Processing Unit |
| FOCUS | Flow Of Communication Upon Society |
| JWAC | Joint Warfare Analysis Group |
| NPS | Naval Postgraduate School |
| RAM | Random Access Memory |
| ROM | Read Only Memory |
| SIG | Social Identity Group |
| TRAC | Training and Doctrine Command Analysis Center |
| TRADOC | Training and Doctrine Command |

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## ACKNOWLEDGMENTS

I would like to recognize Assistant Professor Dr. Camber Warren for his tireless efforts, ingenuity and initiative, which are solely responsible for the completion of this project.

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# SECTION 1. INTRODUCTION

"Conflict Prediction Through Geo-Spatial Interpolation of Radicalization in Syrian Social Media" is a project that was designed to gain valuable spatial-temporal data from social media sources. The results from this initial analysis is intended to eventually support the prediction of acts of collective violence and the radicalization of social identity groups in world regions. It is worthy to note that this project was not able to produce significant results due to the lack of available Syrian datasets. As a result this document will discuss the steps that the study team took to process and analyze large volumes of social media data and show some of the spatial-temporal maps that we were able to produce. However, without a Syrian dataset of violent events or socio-political distribution we cannot make claims about the validity of our results.

## 1.1. BACKGROUND

This project is closely tied to the "Validating the FOCUS Model through an Analysis of Identity Fragmentation in Nigerian Social Media." Both projects represent an effort to utilize social media data to build a spatial-temporal map of nations of interest and gain insights into to social conflicts and segmentation of those nations. Additionally, both projects used the exact same Twitter archive that was purchased through NPS contracting using a Twitter data sales company called GNIP. While both projects had similar purposes, "Validating the FOCUS Model through an Analysis of Identity Fragmentation in Nigerian Social Media" had more successful results because we were able to find an accurate dataset of violent acts in Nigeria. Although there is a Syrian dataset offered through SyriaTracker (SyriaTracker 2015), we were unable to get a copy of that data. The impact of this is that we were unable to populate a dependent variable that would allow us to make insightful conclusions about our ability to use social media to predict conflict inside of Syria. However, we were able to test search concepts and build spatial-temporal maps of Syria in the same way that we were able to do so for Nigeria in the other project.

### 1.2.1. Project History

In April of 2014 TRAC-MTRY had additional projects funds available for research. Dr. Camber Warren from the Defense Analysis department approached TRAC-MTRY with a desire

to research the ability to use social media data to analyze social identity groups in different nations and the capability of social media data to predict violent conflict. TRAC-MTRY and JWAC decided to fund this project by funding the purchase of a 10% random sample of one year's worth of worldwide Twitter data. The funds were transferred to NPS and Dr. Warren purchased the data through GNIP through NPS contracting. Though this project was projected to start in June 2014, the contracting process took much longer than anticipated. Twitter bought GNIP towards the end of the contracting process, which added additional months of contract negotiation. The purchased Twitter data was finally delivered in January 2015 and was the express property of NPS. This data was intended to be used for two initial projects. The first was "Validating the FOCUS Model through an Analysis of Identity Fragmentation in Nigerian Social Media" and the second was "Conflict Prediction Through Geo-Spatial Interpolation of Radicalization in Syrian Social Media." These two projects were highly correlated, which meant that the data management, search algorithms and analysis methodology were nearly identical.

Once NPS received the data Dr. Warren began organizing, processing and analyzing the data. By May, Dr. Warren had created the Python scrips to sort through the data. In August the analysis scripts were complete and Dr. Warren was able to generate informative heat maps of Twitter activity in both Nigeria and Syria and generated an academic paper that explained the process, methodology and results of his initial analytic efforts using Twitter social media. Though these product deliverables marked the end of this project, Dr. Warren is continuing to build on his initial successes and there is tremendous potential for follow on projects that will look to improve on the analytic methods used to gain greater understanding on the social dynamics of nations using social media.

## 1.2. PROBLEM STATEMENT

Can metrics derived from social media content analysis increase the accuracy of our predictions of violent event locations and radicalization?

### 1.2.3. Issues for Analysis.

**Issue 1**: Can Social Media data provide relevant insight into Syria's social dynamic in time and space?

**EEA 1.1.**: Can social media data identify radicalization?

**EEA 1.2.**: Can social media data identify or predict violent conflict?

## 1.3. CONSTRAINTS, LIMITATIONS AND ASSUMPTIONS.

Constraints limit the study team's options to conduct the study. Limitations are a study team's inabilities to investigate issues within the sponsor's bounds. Assumptions are study-specific statements that are taken as true in the absence of facts.

- **Constraints**:
    - Complete by 30 September 2015.
    - Social Media data is limited to Twitter data from August 1st, 2013 to July 31st, 2014.
- **Limitations**:
    - Study is limited to the analysis of Nigeria and Syria in accordance with the approved study proposals.
    - Usable data was limited to geo-coded tweets which represented approximately 27% of the total data repository.
    - Key concepts and metrics were limited to social identity make-up, national identity, social unrest and violent conflict.
- **Assumptions**:
    - Nigeria and Syria provide a relevant test bed for developing theoretical metrics that will help provide insights into the SIGs and social unrest of all nations.
    - Geo-coded tweets provide sufficient representative data to produce relevant analysis on SIG and social unrest.

# SECTION 2. METHODOLOGY

## 2.1. OVERVIEW

This section is meant to be a summary of the methodology employed in this project to gain insight into social identity groups and predict collective violence using social media. For greater detail into the processing and analysis of our archived twitter database refer to the attached technical paper written by Dr. Camber Warren entitled "Mapping the Rhetoric of Violence: Political Conflict Discourse and the Emergence of Identity Radicalization in Nigerian Social Media", which is located in Appendix A.

## 2.2. "BIG DATA"

The data for this research was an archived database of Twitter messages contracted through GNIP. The data represented a 10% random sample of all public messages sent through the Twitter network between 1 August 2013 and 31 July 2014. This archive constituted approximately 12 billion messages and in an uncompressed format was approximately 40 Terabytes. Although tweets are limited to 140 characters of content, the actual twitter file is considerably larger due to embedded metadata. An example of this additional metadata is user identification information, profile information and time and location information. As a part of the GNIP contract our twitter data was augmented with geo-location information in the form of longitude and latitude coordinates. However, roughly only 27% of the files had geo-location information. The implication of this was that only 27% of the data was useful for measuring spatio-temporal subjects from the corpus of information that we possessed (Warren 2015, 9). This usable dataset was further diminished when we began analysis of specific countries.

## 2.3. HARDWARE CONFIGUATION

The sheer size of our archived Twitter database created tremendous challenges for storage and processing. Without sufficient storage and processing hardware the time it would

take to process the 40 Terabytes information could take months of continuous run time. The data storage and processing tools that made this research feasible was a Central Processing Unit (CPU) / Graphic Processing Unit (GPU) hybrid server, designed to emphasize parallel computation and in-memory processing, which is crucial for largescale textual and geospatial analytics. The primary processors consisted of 4 x 12-core Intel Xeon E7-4860v2 CPUs for a total of 48 processing cores, which are capable of parallel processing. Additionally, there were two NVIDIA Tesla K40C GPU processors that equate to 5,760 GPU cores. GPUs have the unique ability to process numbers very quickly (millions of functions per second) and are crucial in high speed graphics and mathematical manipulations. The computer was further augmented with 64 x 32GB DDR3L server memory cards that provided the CPU/GPU with 2 Terabytes of Random Access Memory (RAM). This was perhaps the most critical component built into our CPU/GPU hybrid because it provided an enormous and efficient workbench for data processing. Finally, our CPU/GPU had 8 x 600GB SSD 6 GB/s SATA hard drives that equated to 4.8 terabytes of Read Only Memory (ROM) where the compressed Twitter data was archived. The combination of this hardware setup allowed for very rapid parallel processing that took advantage of very efficient parallel processors that could conduct all data manipulations on a RAM workbench that accelerated processing speeds.

It is worthy to note that initially the we hoped to use the tremendous computational capabilities of the 5,760 GPU cores, but after significant research we discovered that GPUs were limited to mathematical number manipulation which is consistent with the needs of high speed computer graphics, but incompatible with textual analytic. Utilizing GPUs to process textual data is currently an important research topic in industry, but no actionable solutions are available at this time. The result of this discovery was that we were limited to the 48 CPU cores for processing data. Though this was less than what our team hoped it still allowed us to process approximately 500,000 files per second, which equated to approximately seven hours of continuous run time to process the 12 billion files of Twitter data.

### 2.4. ANALYSIS METHODOLOGY

In order to analyze violence and radicalization in Syria, Dr. Warren developed a script in Python that would open each Twitter file and first see if it had a geo-coded location that was

located in Syria and was regionally specific enough to show where in Syria the tweet occurred. These tweets were simultaneously being organized into 1-degree x 1-degree x 1-hour boxes of space-time along with the tweets' content, stored entirely in RAM. These files were organized into a "key-value" store, which means that all records were indexed by a common key structure. The advantage of this setup is that it organizes all keys into a 'hash table', which allows for very fast record look-up speeds, even when the number of underlying records is very large (Warren 2015, 10).

Next, four categories of searchable words were developed to help identify indicators of violence and radicalization. Using the cross-language references in Wikipedia, different spelling variants of the conceptual category "Syria" were identified and scripted into a hash table. This strategy was repeated for conceptual category "Islam" and "ISIS". Finally, a much more complex hash table was built for the concept of 'violence', which included such words as 'stabbing', airstrike', 'soldier', etc. These terms were then translated into Arabic.

With the search categories developed, each Twitter file in our Syrian dataset was searched to identify matches to our search strings. Then we estimated a continuous spatial surface, representing the relative density of messages referencing each concept in a particular place and time using 2-dimensional binned Gaussian kernel density interpolation (Warren 2015, 14). Additionally, the same method was applied to the total Twitter message density to yield an estimated continuous spatial surface for the total Twitter message density. The final values developed were the estimated concept densities divided by the estimated total Twitter message densities over time and space. These five outputs could now be used as five distinct independent variables for statistical modeling. A sampling of the visual representation of these results can be viewed in Figure 1.

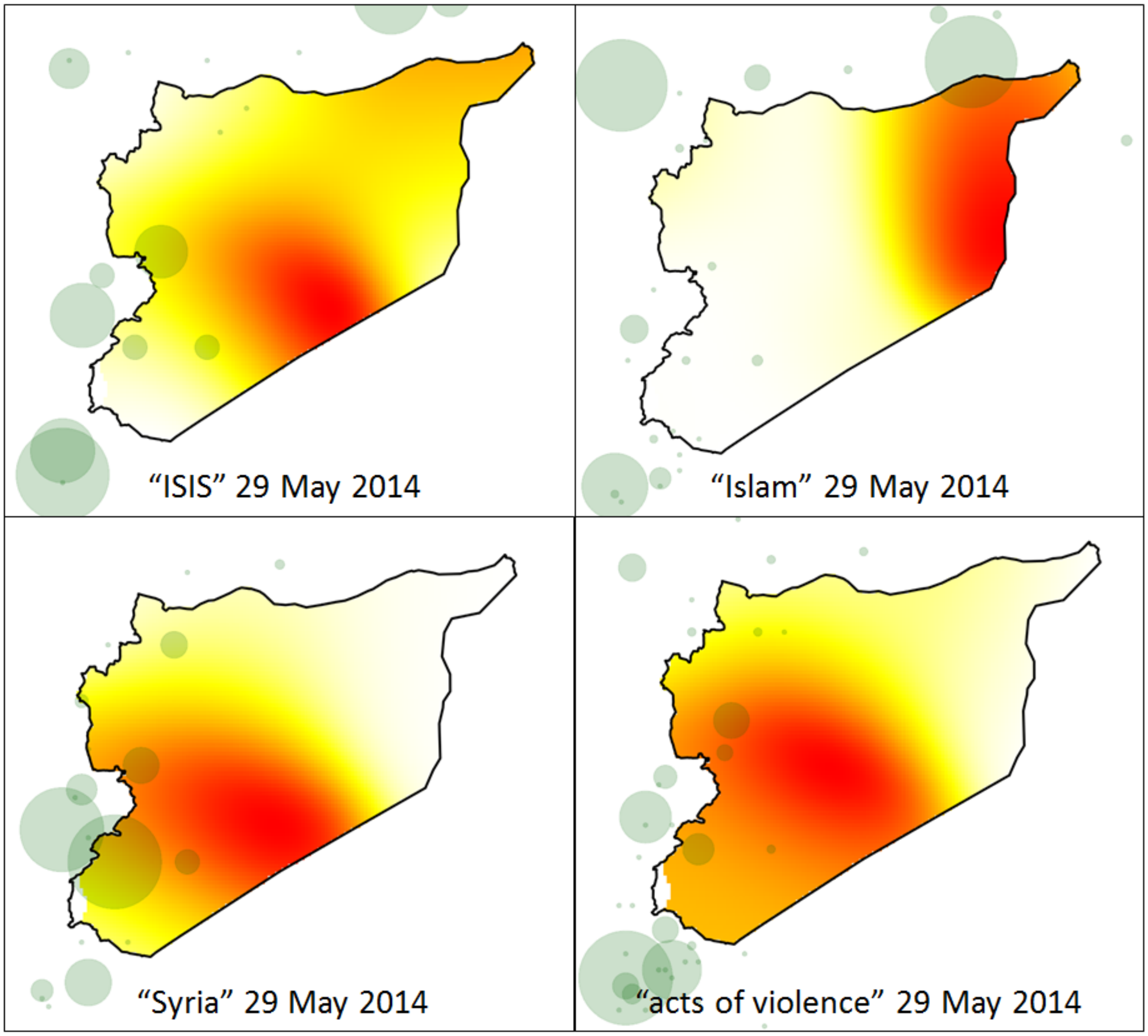


Figure 1. Spatial-Temporal Map of Syria: These maps show the estimated smoothed densities of the concepts of 'ISIS', 'Islam', 'Syria', and 'Violence' on 29 May 2014. Darker colors of red indicate higher densities of the concept; while lighter shades are lower densities (i.e. white is the most extreme low density). The green circles represent the actual Twitter message locations and the size of those circles represents comparative volume size.

In order to gain insight into the relevance of these variables to the modeling of violent conflict and radicalization the team needed an accurate dataset of actual violent conflict of Syria that occurred during the span of our dataset. Unfortunately, no data set was available. We were able to identify a relevant dataset created through online crowd sourcing called SyrianTracker (SyriaTracker 2015), but we were unable to download this dataset or successfully get permission from this organization to use the data. As a result we were unable to populate a dependent

variable that would allow further statistical modeling and thus did not pursue any further analysis. Instead the study team refocused on our parallel project; “Validating the FOCUS Model through an Analysis of Identity Fragmentation in Nigerian Social Media,” because we had already identified a Nigerian data set from the Using the Armed Conflict Location and Event Data Project (ACLED) v5 database (Raleigh 2015). For more information on how we were able to conduct analysis on predicting violent acts using social media data, refer to the technical memo written for the Nigerian study or Dr. Warren’s paper “Mapping the Rhetoric of Violence: Political Conflict Discourse and the Emergence of Identity Radicalization in Nigerian Social Media”, which is located in Appendix A.

# SECTION 3. RESULTS

## 3.1. RESULTS OF ANALYSIS

The results of our analysis were mixed. We were able to demonstrate that we could use social media to build a visual display of social media content in time and space. However, we were unable to show the relevance or accuracy of this data because we were not able to tie it to real-world violent events or socio-political distributions without an accurate dataset of Syria. This would have allowed us to test the significance and accuracy of our measures by populating a dependent variable that could be used in statistical modeling. Although, this was disappointing, I want to highlight that based off of the successful results in our Nigerian social media research we know that the methodology that we have developed is relevant to the modeling and possibly the prediction of violent events in a country. Additionally, the tremendous knowledge that we gained in how to organize and process ‘Big Data’ was a significant success. Our ability to now process billions of files in approximately seven hours will allow us in the future to rapidly analyze numerous topics within the social media realm.

# SECTION 4. RECOMMENDATIONS

This research only represents the earliest phases of research designed to determine the ability of social media data to be used to measure and model events occurring inside national borders. There is tremendous room for expanded research using the principals of spatial-temporal statistical analysis that this project explores. For a start we recommend exploring the scalability of applying social media data to regions of interest. Interesting results could be gained from more refined analysis of cities or districts within a country. Additionally, significant insights could be gained from enlarging the region of interest to multi-country regions and continents. Another important expansion of this research should address to which degree social media discourse is ‘reflective’ or ‘constructive’ in nature. One way to address this could possibly be to model collective violence using social media variables in a time-series approach to see if social discourse can predict collective violence. Lastly, I would recommend repeating this research project once a suitable Syrian dataset of violent events and socio-political distribution becomes available so that we can gain insights into violence prediction and radicalization using statistical modeling techniques.

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Warren, Camber. *Mapping the Rehtoric of Violence: Political Conflict Discourse and the Emergence of Identitiy Radicalization in Nigerian Social Media.* Monterey, CA: Department of Defense Analysis Naval Postgraduate School, 2015.

# APPENDIX A. "MAPPING THE RHETORIC OF VIOLENCE: POLITICAL CONFLICT DISCOURSE AND THE EMERGENCE OF IDENTITY RADICALIZATION IN NIGERIAN SOCIAL MEDIA"

The attached academic paper, written by Assistant Professor Camber Warren, is the foundation for the content of this technical memo. It contains the technical solutions to the research problem that this project addressed and the methods and tools that were used to answer the elements of that problem.

# Mapping the Rhetoric of Violence:

## Political Conflict Discourse and the Emergence of Identity Radicalization in Nigerian Social Media[1]

T. Camber Warren

Department of Defense Analysis
Naval Postgraduate School

CamberW@gmail.com

## Abstract

While there is widespread agreement amongst scholars and practitioners that processes of popular radicalization frequently underlie the generation of insurgent violence, an absence of high-resolution data has prevented existing work from directly validating this relationship. To begin to fill this gap, I seek to leverage new social media technologies to our advantage, by using them as a means of data collection. More specifically, I show that newly developed tools for geo-coding the sending locations of messages sent through the Twitter network, automated estimations of the sentiments expressed in those messages, and spatial interpolation of those estimates, can be used to generate dynamic, data-driven maps of national attachments and political extremism amongst the members of a given population. This approach is applied to the analysis of identity radicalization and fragmentation in Nigeria, over the period August 2013 to July 2014. The results demonstrate that network-analytic metrics derived from spatio-temporal variation in social media content hold substantial promise for enhancing our understanding of the conditions which most favor the emergence of political extremism and collective violence.

[1] Prepared for presentation at the Annual Meeting of the American Political Science Association, Sept. 3rd-6th, 2015, San Francisco, CA.

## Introduction

A burgeoning body of literature increasingly points to the importance of communication dynamics in the generation of armed conflict and collective violence (Pierskalla and Hollenbach 2013; Shapiro and Weidmann 2015; Warren 2014, 2015; Weidmann 2015), and in particular the role played by polarization along newly politicized ethnic cleavages (Bhavnani and Miodownik 2009; Buhaug, Cederman, and Rød 2008; Cederman, Weidmann, and Gleditsch 2011; Cederman, Wimmer, and Min 2010). However, an absence of suitable data has prevented existing work from directly validating the relationship between patterns of political communication and patterns of political violence.

To begin to fill this gap, I seek to leverage new social media technologies to our advantage, by using them as a means of data collection. More specifically, I show that newly developed tools for geo-coding the sending locations of messages sent through the Twitter network, automated estimations of the sentiments expressed in those messages, and spatial interpolation of those estimates, can be used to generate dynamic, data-driven maps of national attachments and political extremism amongst the members of a given population.

As an initial plausibility probe, this approach is applied to the analysis of identity radicalization and fragmentation in Nigeria, over the period August 2013 to July 2014. In particular, I hypothesize that spatio-temporal variation in discursive references to particular conceptual categories will be systematically related to the generation of events of collective violence. Extending the argument presented in Warren (2014) and Warren (2015), I claim that this linkage represents a fundamental mechanism in the production of collective violence. In brief, large-scale violence requires the successful production and dissemination of political ideas justifying that violence. As a result, violence must be spoken into existence, before it can be

enacted. This implies that it may be possible to observe increases in the production of violent rhetoric prior to the emergence of violent acts, and perhaps even to use such measurements to predict the occurrence of collective violence before it erupts in actuality. Moreover, this perspective implies that variation in the basic conceptual categories of political communication could exercise profound effects on the likelihood of large-scale conflict. In regions where political discourse tends to deploy the unifying categories of "nation" and "country", it may be more difficult to generate the kinds of political ideation which justify violence against one's fellow citizens. In contrast, in regions where the dominant discourse revolves instead around narrow sectarian identities, it may be easier for political actors to generate the kinds of animosities that feed spirals of polarized violence. Nigeria provides a particularly interesting window on such dynamics, as the north of the country has recently been characterized by increasingly vociferous mobilization of the "Hausa" ethnic minority, by political actors seeking greater regional autonomy. I will thus examine the following hypotheses:

H1. Spatio-temporal regions with higher levels of violent political rhetoric will experience higher levels of violent political behavior.

H2. Spatio-temporal regions with discourse characterized by more frequent reference to the country of "Nigeria" as a whole will experience lower frequencies of collective violence.

H3. Spatio-temporal regions with discourse characterized by more frequent reference to the "Hausa" minority identity will experience higher frequencies of collective violence.

## The Predictive Power of Social Media

With the surging global popularity of social media platforms, researchers from a variety of disciplines have begun seeking analytic approaches which might allow predictive insights to be derived from social media streams in an unsupervised fashion. While some have focused on the aggregate dynamics of popular culture (Agarwal, Xie, Vovsha, Rambow, et al. 2011; Asur and Huberman 2010; Bae and Lee 2012; Barbosa and Feng 2010; Benhardus and Kalita 2013; Bessi, Caldarelli, Vicario, Scala, et al. 2014; Cataldi, Caro, and Schifanella 2010; Golder and Macy 2011; Hansen, Arvidsson, Nielsen, Colleoni, et al. 2011; Jansen, Zhang, Sobel, and Chowdury 2009; Java, Song, Finin, and Tseng 2007; Kim, Bak, and Oh. 2012; Lerman and Ghosh 2010; Lerman and Hogg 2010; Leskovec, Adamic, and Huberman 2007; Lin, Keegan, Margolin, and Lazer 2014; Morris, Counts, Roseway, Hoff, et al. 2012; Naaman, Boase, and Lai 2010; Naveed, Gottron, Kunegis, and Alhadi 2011; Suh, Hong, Pirolli, and Chi 2010; Wu and Huberman 2007; Wu, Hofman, Mason, and Watts 2011), others have attempted to use metrics derived from individual messages to develop algorithms that 'learn' the underlying sentiments of individual communicators (Abbasi, Chen, and Salem 2008; Agarwal, Xie, Vovsha, Rambow, and Passonneau 2011; Bae and Lee 2012; Barbosa and Feng 2010; Bifet and Frank 2010; Bollen, Pepe, and Mao 2011; Dodds, Harris, Kloumann, Bliss, et al. 2011; Fan, Zhao, Chen, and Xu. 2014; Ghiassi, Skinner, and Zimbra 2013; Golder and Macy 2011; Huang, Peng, Li, and Lee 2013; Jiang, Yu, Zhou, Liu, et al. 2011; Mitchell, Frank, Harris, Dodds, et al. 2013; O'Connor,

Balasubramanyan, Routledge, and Smith 2010; Pak and Paroubek 2010; Stieglitz and Dang-Xuan 2012; Thelwall, Buckley, and Paltoglou 2011; Wang, Can, Kazemzadeh, Bar, et al. 2012). However, both approaches have face serious difficulties in the pursuit of systematic empirical validation. In particular, the lack of any systematic cross-linguistic and cross-cultural 'ground-truth' against which to compare automated sentiment classifications, has generally forced such researchers to limit themselves to single-language (usually English) texts drawn from limited domains (e.g. news reports, movie reviews, etc.).

In contrast, a more recent wave of scholarship has sought to develop metrics geared towards the generation of explicit predictions, which can be compared more directly to observed events. In particular, researchers have shown that mood-based signals drawn from aggregate streams of Twitter messages are partially predictive of swings in financial markets (Bollen, Mao, and Zeng 2011; Zhang, Fuehres, and Gloor 2011, 2012). Along similar lines, a number of researchers have found that political election results can be predicted with some accuracy through relatively simple counts of references to the opposing candidates (Adamic and Glance 2005; Bermingham and Smeaton 2011; Franch 2013; Gayo-Avello 2013; Lassen and Brown 2011; Metaxas and Mustafaraj 2012; Tumasjan, Sprenger, Sandner, and Welpe 2010; Wang, Can, Kazemzadeh, Bar, and Narayanan 2012). While such work has generated more convincing evidence that useful information can be derived from social media streams in an automated fashion, such 'predictions' have generally been limited to relatively simple outcomes, and have been somewhat limited in their ability to shed light on the actual mechanisms underlying the events of interest.

Taking a different angle on social media research, other researchers have sought to use these new communication media as sources of data on the behavior of underlying human

populations. Seen from this perspective, social media represent a new kind of human "macroscope", allowing researchers to measure quantities that would have previously remained opaque to observation, at a scale and resolution that would have previously been impossible to achieve. In this way, social media can serve as a new tool for developing enhanced understanding of the fundamental mechanisms underlying human social and political interactions. For instance, a number of works have begun investigating how cultural products achieve popularity, examining both the content-level and context-level factors that lead messages to be repeated, and developing new models of the dynamics of information diffusion (Aral and Walker 2012; Bakshy, Hofman, Mason, and Watts 2011; Bliss, Kloumann, Harris, Danforth, et al. 2012; Boyd, Golder, and Lotan 2010; Cha, Haddadi, Benevenuto, and Gummadi 2010; Dodds, Harris, Kloumann, Bliss, and Danforth 2011; Eisenstein, O'Connor, Smith, and Xing 2014; Golder and Yardi 2010; Golub and Jackson 2010; Gomez, Manuel, and Krause 2010; Hansen, Arvidsson, Nielsen, Colleoni, and Etter 2011; Kwak, Lee, Park, and Moon 2010; Pfitzner, Garas, and Schweitzer 2012; Romero, Meeder, and Kleinberg 2011; Shamma, Kennedy, and Churchill 2011; Stieglitz and Dang-Xuan 2012; Zaman, Herbrich, Gael, and Stern 2010). In a similar vein, researchers have begun to examine the forces underlying the generation of 'collective attention', combining empirical measures with simulation models of competition between 'memes', to examine the operation of ecological constraints on message reproduction (Benhardus and Kalita 2013; Cataldi, Caro, and Schifanella 2010; Hong and Davison 2010; Jungherr and Jurgens 2013; Lehmann, Gonçalves, Ramasco, and Cattuto 2012; Mehrotra, Sanner, Buntine, and Xie 2013; Mei, Liu, Su, and Zhai 2006; Sasahara, Hirata, Toyoda, Kitsuregawa, et al. 2013; Weng, Flammini, Vespignani, and Menczer 2012; Wu and Huberman 2007), while others have used data from social media streams to build models of the mechanisms

underlying the formation and dissolution of social ties between individuals (Bollen, Gonçalves, Ruan, and Mao 2011; Bond et al. 2012; Coviello et al. 2014; Fan, Zhao, Chen, and Xu. 2014; Frank, Mitchell, Dodds, and Danforth 2012; Golder and Yardi 2010; Gonzalez, Cuevas, Cuevas, and Guerrero 2011; Himelboim, McCreery, and Smith 2013; Kuehn, Martens, and Romero 2014; Lazer et al. 2009; Mitchell, Frank, Harris, Dodds, and Danforth 2013; Mutz 2002; Shalizi and Thomas 2011; Zamal, Faiyaz, and Ruths 2012)

Increasingly, such efforts are also being applied to the political domain, yielding substantial new insights into the dynamics of public opinion, electoral competition, and political persuasion (Adamic and Glance 2005; Ausserhofer and Maireder 2013; Barberá and Rivero 2014; Barberá 2014, 2015; Barberá, Jost, Nagler, Tucker, et al. 2015; Bermingham and Smeaton 2011; Bond and Messing 2015; Chadwick 2006, 2013; Conover et al. 2011; Conover, Gonçalves, Flammini, and Menczer 2012; Conover, Gonçalves, Ratkiewicz, Flammini, et al. 2011; DiGrazia, McKelvey, Bollen, and Rojas 2013; Farrell 2012; Feller, Kuhnert, Sprenger, and Welpe 2011; Golbeck and Hansen 2014; Grossman, Humphreys, and Sacramone-Lutz 2014; Himelboim, McCreery, and Smith 2013; Lawrence, Sides, and Farrell 2010; Monroe, Colaresi, and Quinn 2008; Mustafaraj, Finn, Whitlock, and Metaxas 2011, 2011; Parmelee and Bichard 2012; Prior 2007; Ringsquandl and Petkovic 2013; Shirky 2011; Stieglitz and Dang-Xuan 2012; Wojcieszak and Mutz 2009; Yardi and Boyd 2010). In addition to the study of 'normal' politics, researchers are also increasingly using metrics derived from social media to shed new light on the dynamics of social mobilization, political polarization, and collective violence (Aday et al. 2010; Bailard 2015; Brandt, Freeman, and Schrodt 2011, 2014; Colbaugh and Glass 2012; Conover et al. 2013; Gleason 2013; Gohdes 2015; Hammond and Weidmann 2014; Howard and Hussain 2013, 2011; Hussain and Howard 2013; Lotan, Graeff, Ananny, Gaffney, et al. 2011;

Martin-Shields and Stones 2014; Metternich, Dorff, Gallop, Weschle, et al. 2013; Metzger et al. 2014; Munger 2014; Pierskalla and Hollenbach 2013; Ramakrishnan et al. 2014; Ritter and Trechsel 2014; Schroeder, Everton, and Shepherd 2014; Shapiro and Weidmann 2015; Siegel 2014; Theocharis 2013; Tudoroiu 2014; Tufekci and Wilson 2012; Wang, Gerber, and Brown 2012; Ward et al. 2013; Warren 2015; Windt and Humphreys 2014; Wolfsfeld, Segev, and Sheafer 2013; Zeitzoff, Kelly, and Lotan 2015; Zeitzoff 2013). Moreover, while such research has generally found that such technologies decrease stability in weak-state environments, other researchers have pointed to the ability of authoritarian governments to also turn such tools to their advantage (Gohdes 2015; Howard, Agarwal, and Hussain 2011; Kalathil and Boas 2003; King, Pan, and Roberts 2013; Lynch 2011; Morozov 2011; Munger 2014; Rød and Weidmann 2015).

**A Spatio-Temporal Approach**

In most of the analyses reported above, metrics were calculated based on units of analysis characterized by individual users, or individual messages. The difficulty with such approaches, when attempting to make statistical judgements concerning the underlying population, is that the sample is likely to be strongly biased along a number of dimensions. It is well known that use of social media correlates with a number of demographic characteristics, including age and wealth, and that social media users are therefore unlikely to provide a fully representative sample of the underlying population (Ansolabehere and Hersh 2012; Barberá and Rivero 2014; Mislove, Lehmann, Ahn, Onnela, et al. 2011). As a result, metrics for which "users" are in the denominator (i.e. positive messages per user per day) are likely to be similarly biased.

The approach adopted here is instead to characterize the relevant metrics as functions of space-time units, rather than as proportions of users. Here, I take inspiration from recent work which has shown improvements in our abilities to make automatic judgements of geographic location from unstructured text in Twitter user profiles (Blanford, Huang, Savelyev, and MacEachren 2015; Cheng, Caverlee, and Lee 2010; Compton, Jurgens, and Allen 2014; Conover et al. 2013; Hawelka et al. 2014; Kaltenbrunner et al. 2012; Kulshrestha, Kooti, Nikravesh, and Kp. 2012; Lee and Sumiya 2010; Leetaru, Wang, Cao, Padmanabhan, et al. 2013; Mitchell, Frank, Harris, Dodds, and Danforth 2013; Nemeth, Mauslein, and Stapley 2014; Takhteyev, Gruzd, and Wellman 2012; Yuan, Cong, Ma, Sun, et al. 2013). This approach allows researchers to greatly expand the sample of Twitter messages which can be geo-referenced (from around 2% to 27%), by avoiding the need for GPS coordinates, and instead relying on the user-reported hometowns from their public profiles.

The starting point for this analysis is an archived database of Twitter messages, representing a fully randomized 10% sample of all public messages sent through the Twitter network between August 1st, 2013 and July 31st, 2014; approximately 12 billion messages in total.[2] In uncompressed format, this archive represents approximately 40 Terabytes of textual data, and so the very scale which offers this new "macroscope" also represents a challenge for standard computational approaches, which search across strings in serial order. The solution adopted here is to script the production of "in-memory" database indexes, organized to reflect bins of space, time, and other nested concepts. In particular, I utilize what is known as a "key-value" store, which means that all records are indexed by a common key structure, which is just

[2] Archive licensed through agreement between Twitter, Inc. and the U.S. Naval Postgraduate School, as part of the "Global Data Initiative." See www.camberwarren net/gdi.

a string describing membership in some set of containers in which many individual records are stored. The database is a modified version of the open-source Aerospike database,[3] which I have expanded to allow for highly-parallelized loading of data into RAM, by creating separately threaded communication channels for each logical CPU core in the system, allowing 'swarms' of parallel computational workers to operate in tandem, and avoid resource conflicts, without the need for hierarchical control structures. The advantage of this setup is that it organizes all keys into a 'hash table', which allows for very fast record look-up speeds, even when the number of underlying records is very large.

Our first task is to use this memory structure to reference each message to a location in space, given by latitude and longitude coordinates. To do so, I draw on data from the geonames.org gazetteer, an open-source database of named geographic places. The database contains references to over 10 million individual locations, with latitude and longitude coordinates, in addition to over 2 million alternate names and spellings, spanning over a 100 languages. Converting this information into a searchable form requires first 'tokenizing' the individual strings into meaningful chunks (i.e. words and phrases). This process is relatively straightforward for English, as it makes consistent use of spaces to differentiate words. However, this pattern is far from universal in other languages. For instance, ideographic languages such as Chinese and Japanese generally use long strings of characters with no spaces in between words, while Vietnamese uses spaces in between each syllable of a single word. Moreover, sometimes atomic concepts, such as "China", are represented by 'words' composed of

[3] See http://www.aerospike.com/. The database application also makes use of a modified version of the UltraJSON python library (https://github.com/esnme/ultrajson), which I have expanded to allow for bulk parsing of large, multiline text files, and a modified version of the RE2 python library (https://github.com/facebook/pyre2/), expanded to allow for grouped regular expression pattern matching using hierarchically nested terms. All modified source code will be redistributed on an open-source basis. Contact author for details.

one, two, three, or more ideographic characters. In Cambodian, a number of common place names require as many as eight ideographic word-characters to write the string referring to a single city. Thus, the very notion of what counts as a "word" or "phrase" is difficult to generalize across languages. The solution generally adopted in the works cited above, has been to either ignore the problem by focusing on English place names, or to develop language-specific parsers for particular applications. But this requires expensive computations, as each parser must actually read and make sense of the string in order to determine the proper word/phrase boundaries, and so cannot be feasibly implemented for search across a large number of languages simultaneously.

Instead, I construct a generic multilingual phrase index by segmenting each text string arbitrarily, without expending any effort to 'read' or make semantic sense of the underlying text. To do so, I make use of a particular text encoding format, known at "UTF-8", which has the advantage of coding all characters in fixed-size arrays of bytes. A roman letter, such as "a" for instance, is stored in a single byte, whereas nearly all ideographic characters in common use are stored as either 3 bytes or 6 bytes. This means that whereas roman scripts can be split into words by breaking at every space, ideographic scrips can be broken into potential words by splitting the string in byte lengths of multiples of 3. Some of the resulting sub-strings will be nonsense, but they can be easily screened out by attempting to re-encode the bytes as valid UTF-8 characters, and discarding any uninterpretable sub-strings. Arbitrary phrases are thus constructed from each string by first splitting at every space, and then taking any remaining non-roman characters and extracting all unique substrings with lengths equal to multiples of 3, and then concatenating the resulting words into space-separated sequences (i.e. 'phrases') consisting of all unique sub-sequences with length less than some maximum phrase length. I in the results reported below, I

allow for phrase lengths up to 9 'words', to account for difficult strings such as "*Cộng hòa Xã hội chủ nghĩa Việt Nam*", which is the name of the country of "Vietnam" written in Vietnamese, and "ក្រុងភ្នំពេញ", which is the name of the city of "Phnom Penh" written in Cambodian. Each of these phrases is then separately indexed in an in-memory hash table, as described above. The result is a search index composed of approximately 23 million unique text phrases.

Input search strings are taken from the "Location" field associated with each Twitter message, which is simply a box into which users can type free-form descriptions of the location (usually a hometown) from which they are sending their messages. These input strings are tokenized through the same procedure, allowing one-to-one matching of exact phrases. When multiple matching strings are found, the algorithm narrows the potential matches by first checking for nested overlaps between administrative units, such as "Ohio", and specific places, such as "Springfield", and then prioritizes matches to more specific places over matches to more general areas. To break further ties, the algorithm then relies on a simple measure of the "salience" of the information in the search result, by assigning a score to each potential match, given by:

$$S_i = \left(\sqrt{P+1}\right)(L^2)$$

where $P$ is the total population of the place, as recorded in the Geonames database, and $L$ is the byte-length of the matching character string.

For each record, we first check whether GPS coordinates are available (less than 2% of the sample), and if they are not then we attempt to match any location text using the procedure described above. Records for which no matching locations can be found, or which can only be matched at level of countries or top-level administrative units, are discarded. The remaining records (approximately 27% of the original sample) are then parsed, assigned latitude, longitude,

and timestamp coordinates, and stored in a separate key-value database, in which the keys are given by unique combinations of discrete units of space and time. In this way, the keys of the database function as spatio-temporal indexes, allowing for high-speed access of chunks of records defined by discrete ranges of time and space. The chunks are defined in units of latitude/longitude degrees and hours, so that each storage bin holds the records for a 1-degree x 1-degree x 1-hour box of space-time. The result is an in-memory structured representation of each record, stored entirely in RAM, recording the full text of each message, the estimated geo-coordinates of the user's sending location, and the date and time when the message was sent.

Using this approach, I identify 14,322,348 separate Twitter messages sent from within the boundaries of Nigeria, between August 1$^{st}$, 2013 and July 31$^{st}$, 2014. This set of records forms the basis for the results reported below. In order provide predictive leverage on the location and timing of violent events, I seek to side-step the thorny issues associated with cross-cultural interpretations of complex symbols, attitudes, and sentiments, and focus instead on discursive references to particular "concepts", for which more rigorous bounds can be defined on a cross-cultural basis. In particular, I aim to capture simple indicators of three concepts, with differing levels of complexity: (1) a country ("Nigeria") understood a fixed referent by those familiar with the term, (2) a group ("Hausa") representing a locus of recent political struggle, and (3) a category of action ("armed conflict") which can be objectively defined but which is described in practice through a wide array of terms.

The concepts of "Nigeria" and "Hausa", while complex in a sociological sense, are relatively easy to search for in text form. Even across the major linguistic communities in Nigeria, these terms tend to be spelled in approximately the same way. Using the cross-language references in Wikipedia, I identify seven local spelling variants for "Nigeria" ('nijeriya',

'najeriya', 'naìjíríyà', 'naijiria', 'naigeria', 'nàìjíríà', and 'naijiriya') and four local spelling variants for "Hausa" ('bahaushe', 'bahaushiya, 'hausawa', and 'haoussa').

The concept of "armed conflict", in contrast, represents a more difficult search task, as it can be referenced through a wide variety of specific objects and actions (e.g. 'stabbing', 'airstrike', 'soldier', etc.), all of which need to be jointly recognized as members of the overarching concept. To accomplish this on a cross-linguistic basis, I first cross reference existing lexicons (Harvard Inquirer, MPQA) to develop a list of 366 English language terms representing direct references to objects and actions associated with armed conflict (see Appendix), taking care to include all forms of relevant nouns and verbs. I then use scripted access to the Google Translate API (https://translate.google.com/) to attempt to translate each term into the five most common non-English languages in Nigeria: French, Arabic, Hausa, Igo, and Yorbua. The results of this machine translation exercise are shown in Table A1, with blank cells indicating either that no translation was possible or that the original term was selected as the best translation. As can clearly be seen, the French and Arabic translations achieve more thorough coverage than the smaller Nigerian languages, but there is good general coverage across all concepts and languages. Collapsing this table into a searchable index yields 1,195 unique search strings, which are stored and indexed in a separate database using the tokenization procedures described above.

For each concept and each day, I estimate a continuous spatial surface, representing the relative density of messages referencing that concept in a particular place and time. The smoothing is conducted using 2-dimensional binned Gaussian kernel density interpolation. For each concept, for each day I estimate a separate smoothed density, treating as separate points each message containing the concept, and then calculate a separate smoothed density surface

using the full sample of messages, regardless of content. The final values reported for each concept are then the concept density estimated at a given location in space-time, divided by the total estimated message density at that location. The result is a smooth surface estimating the likelihood that a given location will produce a token of a given concept, relative to the total volume of tokens produced at that location.

Figure 1 shows a color-scale representation of the smoothed densities of total message volume and the relative densities of the concepts of “Nigeria” and “Hausa”, on days at the beginning, middle, and end of our period of study, with red indicating higher levels and yellow indicating lower levels. The green circles show the actual locations of the messages used to produce the smoothed surfaces, with larger bubbles representing a greater volume of messages. As can clearly be seen, these metrics generate substantial content-based variation which is not simply reflective of the underlying volume of messages. Moreover, the geographic distribution of references to these terms varies significantly, with references to “Hausa” occurring much more frequently in the north of the country where Hausa communities represent a larger proportion of the population.

**Statistical Models and Results**

In order to draw inferences regarding the relationship between these metrics and the emergence of collective violence, I estimate heterogeneous point process models with a Strauss inter-point interaction function designed to flexibly capture patterns of spatial autocorrelation without forcing the analyst to pre-specify spatial units at any particular resolution (see Warren (2015) for a discussion). The dependent variable is measured using the ACLED v5 database, from which I build a list of the locations of all violent armed conflict events occurring within

Nigeria, from September 1st, 2013 to July 31st, 2014 (n = 1,427). For each event, covariate values are associated with the event by taking the daily smoothed surfaces described above and averaging across a temporal window stretching back over the previous 30 days. Randomly generated control points generated for statistical inference are spread evenly within this space-time box. Regression modelling then proceeds by comparing the covariate distributions observed at the random controls points, to the covariates observed at the actual event locations.

The results are presented in Table 1. Model 1 is a baseline specification which includes only total message density and the interpoint interaction function. Model 2 adds in the covariate surfaces capturing the relative density of our concepts, “armed conflict”, “Nigeria”, and “Hausa.” Finally, Model 3 add an interaction terms between “Nigeria” and “Hausa.” Taken as a whole, the results demonstrate that substantial predictive leverage can be gained through metrics derived from the content of social media messages. Comparing Model 1 to Model 2, we can that the AIC score improves with the addition of our content-based metrics, indicating that the results are not driven simply by differences in the penetration of the medium in different areas of the country. Rather, it appears that variation in the content of the messages provides additional predictive leverage over the likely locations of armed conflict events. In particular, the positive and statistically significant ($p < 0.001$) coefficient for “armed conflict” indicates that areas where people speak with more violent discourse are also areas that are more likely to generate actual events of violence. Moreover, the negative and significant coefficient for “Nigeria” ($p < 0.01$) indicates that areas where people make more frequent references to the country as a whole are less likely to generate internal collective violence. In contrast, the positive and significant coefficient for “Hausa” ($p < 0.001$) indicates that discursive references to this polarizing sectarian identity are systematically associated with higher levels of actual violence. Finally, the

positive and significant results for the interaction term between “Nigeria” and “Hausa” ($p < 0.001$) indicates that the most violent-prone configuration of these variables occurs in areas where “Nigeria” and “Hausa” are referenced with high joint density.

## Conclusion

The results presented here thus provide new evidence for the importance of communication dynamics in the production of collective violence. Moreover, they demonstrate that it is possible, even with very simple metrics, to begin to differentiate forms of collective discourse that are more prone to be associated with actual events of collective violence. In particular, the evidence presented here indicates that discourses revolving around integrative national identities are likely to be less prone to the generation of collective violence than discourses that focus on divisive sectarian identities, while also pointing to the possibility that it is actually the confluence of these categories that is most strongly associated with the production of violence.

However, based on the very preliminary results presented here, a number of questions remain. While these associations generate substantial predictive leverage, it is not clear whether they arise due to “reflective” mechanisms, through which discourse comes to mirror existing events on the ground, or due to “constructive” mechanisms, through which discourse produces events that would not otherwise have occurred. Moving forward, closer attention to the temporal dynamics underlying these processes may make it possible to begin to disentangle the direction of these causal arrows.

**Figure 1. Relative Spatio-Temporal Density of Discursive Concepts**

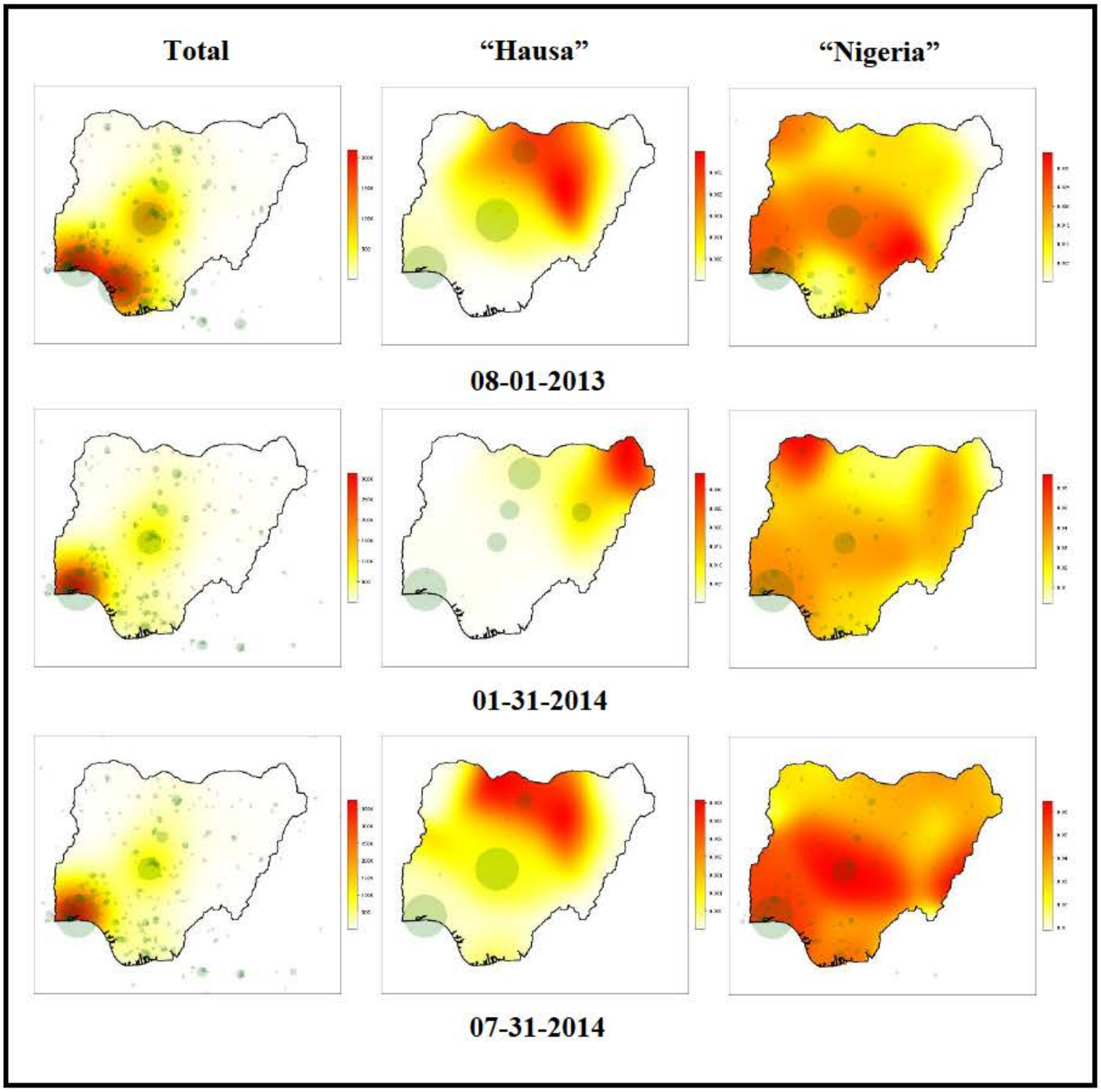

**Table 1. Point Process Models of Violent Event Locations**

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| **Total Density** | 8.1990 | *** | 13.5342 | *** | 25.6532 | *** |
| | (1.1181) | | (2.7577) | | (3.2742) | |
| **"armed conflict"** | | | 3.2000 | *** | 3.3299 | *** |
| | | | (0.3618) | | (0.3698) | |
| **"Nigeria"** | | | -0.8351 | ** | -4.4354 | *** |
| | | | (0.3105) | | (0.5416) | |
| **"Hausa"** | | | 0.1518 | *** | -1.2323 | *** |
| | | | (0.0246) | | (0.1806) | |
| **"Nigeria" x "Hausa"** | | | | | 1.7509 | *** |
| | | | | | (0.2226) | |
| **Intercept** | 1.6191 | *** | -0.8584 | * | 2.0897 | *** |
| | (0.1284) | | (0.3770) | | (0.5674) | |
| **Interpoint Interaction** | 0.0027 | *** | 0.0024 | *** | 0.0022 | *** |
| | (0.0003) | | (0.0004) | | (0.0004) | |
| **AIC** | -3882.43 | | -3917.65 | | -3984.23 | |

Note: Coefficients from heterogeneous point process models. Standard error in parentheses.
*p < 0.05, **p < 0.01, ***p < 0.001

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# Appendix

## Table A1. Nigerian Multilingual Dictionary of “armed conflict”

| English | Arabic | French | Hausa | Igbo | Yoruba |
|---|---|---|---|---|---|
| aggression | عدوان | agression | ta'adi | awakpo | ifinran |
| aggressions | الاعتداءات | agressions | ta'addancin | | |
| aggressor | معتدي | agresseur | tsokanar zalunci | ocho | |
| aggressors | المعتدين | agresseurs | tsõkana | ebido | |
| airstrike | غارة جوية | raid aérien | harin jirgin sama | | |
| airstrikes | الضربات الجوية | frappes aériennes | harin na jiragen | | |
| ak 47 | | | | | |
| ak47 | | | | | |
| ambush | كمين | embuscade | kwanto | | |
| ambushed | كمين | embuscade | kwanton | echechiela | nibon |
| ambushes | الكمائن | embuscades | kwanton bauna | nēru nbì | ẹbu |
| ambushing | نصب الكمائن | embuscade | | | |
| annihilate | إبادة | annihiler | warware | ekpochapụ | |
| annihilated | يباد | anéanti | shafe | n'iyi | ọdi |
| annihilates | يقضي | annihile | shafe | | |
| annihilating | مهلك | annihilant | halakar | kpochapụ | |
| annihilation | إبادة | | rushewa | ebibi | |
| antagonism | تضاد | antagonisme | abotar gaba | imegidesi | |
| antagonist | خصم | antagoniste | | na-eti ọkpọ | |
| antagonists | الخصوم | antagonistes | | na-akụ ọkpọ | |
| armament | تسلح | armement | makamai | nke zaịọn | iham |
| armaments | التسلح | armements | | ngwá agha | |
| armed | مسلح | armé | | agha | ologun |
| armies | الجيوش | armées | sojojin | ụsụụ ndị agha | ogun |
| arming | تسليح | armement | tara makamai | igbochi ngwá agha ijupụta | |
| armored | مدرع | blindé | sulke | | |
| armoured | مدرع | blindé | sulke | | |
| army | جيش | armée | sojojin | agha | ogun |
| artillery | المدفعية | artillerie | manyan bindigogi | ogbunigwe | |
| assassinate | اغتيال | assassiner | kisa | igbu mmadu | |
| assassinated | اغتيال | assassiné | kashe | egbu | |
| assassinates | تغتال | assassine | | | |
| assassinating | اغتيال | assassinant | kisan gilla | | |
| assassination | قتل | assassinat | kisan gilla | mgbu mmadu | |
| assassinations | الاغتيالات | assassinats | aikata kashe-kashen | | ipania |
| assault | اعتداء | agression | hari | wakpo | sele si |
| assaulted | اعتداء | agressé | auka | tiri | nri ipalara |
| assaulting | الاعتداء | assaut | | n'ịwakpo | |
| assaults | الاعتداءات | agressions | hari | ẹma ẹsịn | |
| attack | هجوم | attaque | hari | agha | kolu |
| attacked | هاجم | attaqué | sun kai hari | wakpoo | kolu |
| attacker | مهاجم | attaquant | | ebibi | |
| attackers | المهاجمين | attaquants | maharan | kpara | |
| attacking | مهاجمة | attaquer | kai hare hare | awakpo | bàa |
| attacks | هجمات | attaques | kai hare-hare | ọgụ | ku |
| barricade | متراس | | barikadi | mgbochi | |
| barricaded | تحصن | barricadé | | mechibido | |
| barricades | المتاريس | | | | |
| barricading | باعتراض | bastingages | | imechibido | |
| battalion | كتيبة | bataillon | bataliya | | ẹwú |
| battalions | كتائب | bataillons | | | ọrọrún |
| battle | معركة | bataille | yaƙi | agha | ogun |
| battled | اشتبكت | lutté | fama | agha | |
| battlefield | ساحة المعركة | champ de bataille | fagen fama | n'ọgbọ agha | ogun |

## Table A1 (cont.) Nigerian Multilingual Dictionary of "armed conflict"

| English | Arabic | French | Hausa | Igbo | Yoruba |
|---|---|---|---|---|---|
| battlefields | ساحات القتال | champs de bataille | fagen | | |
| battlefront | جبهة القتال | | | | |
| battlefronts | جبهات القتال | champs de bataille | | | |
| battleground | ساحة المعركة | champ de bataille | a fafata | agha | |
| battlegrounds | معارك | champs de bataille | dauki ba dadi | | |
| battles | المعارك | batailles | fadace-fadace | agha | ogun |
| battleship | سفينة حربية | navire de guerre | jirgin ruwa na soja | agha | |
| battleships | البوارج | cuirassés | | | |
| battlespace | المعركة | bataille | | | |
| battlespaces | | espaces de combat | | | |
| battling | تقاتل | combattre | | alụ | njijadu |
| behead | قطع رأسه | décapiter | | | |
| beheaded | قطع رأس | décapité | fille kansa | isi | bẹ |
| beheading | قطع رأس | décapitation | fille | | |
| beheadings | قطع الرؤوس | décapitations | | | |
| belligerent | دولة محاربة | belligérant | | mmụọ ịlụ ọgụ | |
| belligerents | المتحاربين | belligérants | | | |
| bled | نزف | saigné | zub da jini | | leemoô |
| bleed | ينزف | saigner | jinni | igba obara | |
| bleeding | نزيف | saignement | na jini | ọbara ọgbụgba | ẹjẹ |
| bleeds | ينزف | saigne | | | |
| blockade | حصار | blocus | kawancen | mgbochi | |
| blockaded | المحاصر | bloqué | | nọchibidoro anọchibido | |
| blockades | الحصار | blocus | | | |
| blockading | حصار | blocus | | | |
| blood | دم | sang | jini | ọbara | ẹjẹ |
| bloodshed | سفك الدماء | effusion de sang | zubar da jini | na-awụfu ọbara | |
| bloodstain | بقع دم | tache de sang | | | |
| bloodstained | ملطخة بالدم | taché de sang | | ọbara tetọrọ | |
| bloodstains | بقع الدم | taches de sang | | ọbara | |
| bloody | دام | sanglant | na jini | ọbara | itajesile |
| bomb | قنبلة | bombe | bam | bọmbụ | bombu |
| bombed | قصف | bombardé | bamai | tụrụ bọmbụ | |
| bomber | مهاجم | bombardier | | otu bombu | |
| bombers | المفجرين | bombardiers | kai harin | atụ bọmbụ | |
| bombing | قصف | bombardement | bom | bọmbụ | bombu |
| bombings | تفجيرات | attentats à la bombe | bom | | |
| bombs | القنابل | bombes | ragargaza | | ado- |
| brigade | لواء | | birged | brigeedi | ẹgbẹ ọmọ ogun |
| brigades | ألوية | | | | |
| bullet | رصاصة | balle | harsashi | | ibọn |
| bullets | الرصاص | balles | harsasai | mgbọ | awako |
| casualties | خسائر | victimes | jikkata | onwu | faragbogbe |
| casualty | الإصابات | victime | mai hasara | a na-egbu | |
| combat | قتال | | fama | ọgụ | ija |
| combatant | مقاتل | combattant | | n'Ịlụ Agha | |
| combatants | المقاتلين | combattants | | na-alụ agha | ogun |
| conflict | صراع | conflit | rikici | esemokwu | rogbodiyan |
| conflicts | الصراعات | conflits | rikice-rikice | esemokwu | ija |
| confrontation | مواجهة | affrontement | adawa | | |
| confrontations | مواجهات | | | ese okwu | |
| coup | انقلاب | | juyin mulki | kuu | |
| coups | الانقلابات | | juyin mulki ne | | |
| damage | ضرر | dommage | | mmebi | bibajẹ |
| damaged | التالفة | endommagé | lalace | mebiri emebi | ti bajẹ |
| damaging | ضررا | dommageable | tareda žata | emebiri | ọmọde |
| dead | ميت | mort | matattu | nwụrụ anwụ | okú |

## Table A1 (cont.) Nigerian Multilingual Dictionary of "armed conflict"

| English | Arabic | French | Hausa | Igbo | Yoruba |
|---|---|---|---|---|---|
| deadly | قاتل | mortel | | na-egbu egbu | oloro |
| death | الموت | décès | mutuwa | ọnwụ | iku |
| deaths | وفيات | décès | mutuwar | ọnwụ | iku |
| decapitate | ضرب العنق | décapiter | | | |
| decapitated | مقطوعة الرأس | décapité | | | |
| decapitates | يقطع رأس | décapite | | | |
| decapitating | قطع رأس | décapitant | | | |
| decapitation | قطع الرأس | décapitation | | | |
| destroy | هدم | détruire | halaka | ebibi | |
| destroyed | دمرت | détruit | halakar | ebibi | |
| destroyer | مدمر | destructeur | hallakarwa | mbibi | apanirun |
| destroyers | مدمرات | | hallaka | ebukọrọ | awọn afinișeiję |
| destroying | تدمير | détruisant | hallaka | ebibi | dabaru |
| destroys | يدمر | détruit | halaka | ebibie | |
| destruction | تدمير | | halaka | mbibi | iparun |
| die | يموت | mourir | mutu | anwụ | kú |
| died | توفي | mort | ya rasu | nwụrụ | kú |
| dies | يموت | meurt | mutu | na-anwụ anwụ | ku |
| dismember | يمزق | démembrer | | | |
| dismembered | تقطيع اوصالها | démembré | | emekwa | |
| dismembering | تمزيق | équarrissage | | | |
| dismembers | يقطع أوصال | démembre | | | |
| dying | الموت | mourant | mutuwa | na-anwụ anwụ | ku |
| enemies | الأعداء | ennemis | makiyan | iro | ọtá |
| enemy | العدو | ennemi | maƙiyi | onye iro | ọtá |
| explosion | انفجار | | fashewa | gbawaranụ | bugbamu |
| explosive | مادة متفجرة | explosif | | mgbawa | ibęjadi |
| explosives | متفجرات | explosifs | nakiyoyi | | |
| fatal | قاتلة | | | egbu egbu | apani |
| fatalities | وفيات | décès | | anwụ | |
| fatality | نكبة | fatalité | | ọdachi | |
| fatally | على نحو مهلك | mortellement | | gbagburu | |
| feud | عداء | querelle | gaba | esemeokwu | orilede |
| feuded | احتدام | rivalisait | | | |
| feuding | المتناحرة | vendetta | husuma | | mu awoôn |
| feuds | الحزازات | querelles | | | |
| fight | عراك | bats toi | yaki | agha | ija |
| fighter | مقاتل | combattant | jirgin saman soja | | onija |
| fighters | مقاتل | combattants | mayakan | alụso | awọn onija |
| fighting | القتال | combat | fada | ọgụ | ija |
| fights | المعارك | combats | ta faɗa | ịlụ ọgụ | njà |
| firearm | سلاح ناري | arme à feu | | | ohun ija |
| firearms | الأسلحة النارية | armes à feu | bindigogi | eji égbè agbagbu | ibon |
| firefight | معركة | fusillade | | | |
| firefights | معارك | des échanges de tirs | | | |
| force | قوة | | karfi | ike | agbara |
| forces | القوات | | sojojin | agha | ologun |
| fought | قاتل | combattu | suka yi jihãdi | agha | ja |
| grave | قبر | tombe | kabari | ili | sin |
| graves | المقابر | tombes | kaburbura | ili | ibojì |
| grenade | قنبلة يدوية | | gurnati | bombu | |
| grenades | قنابل | | gurnetin | | |
| guerillas | حزب | guérilleros | dakarun | agha okpuru | |
| guerrilla | حرب العصابات | guérilla | yaƙin | okpuru | |
| gun | بندقية | pistolet | bindiga | egbe | ibon |
| gunboat | زورق حربي | canonnière | | | |
| gunboats | الزوارق الحربية | canonnières | | | |

## Table A1 (cont.) Nigerian Multilingual Dictionary of “armed conflict”

| English | Arabic | French | Hausa | Igbo | Yoruba |
|---|---|---|---|---|---|
| gunfire | إطلاق نار | des coups de feu | bindigar | | |
| gunman | مسلح | tireur | | | |
| gunmen | مسلحون | des hommes armés | yan bindiga | | |
| gunned | قتل | abattu | | | |
| gunner | مدفعي | canonnier | sojan igwa | onye agha | |
| gunners | المدفعية | canonniers | | | |
| gunning | علم المسدسات | | | | |
| gunpowder | بارود | poudre à canon | | | |
| guns | البنادق | pistolets | bindigogi | egbe | ibon |
| gunship | حربية | | | | |
| gunships | طائرات | hélicoptères de combat | | | |
| gunshot | إطلاق نار | coup de feu | harbin bindiga | | ìbọn |
| gunshots | طلق ناري | des coups de feu | bindigogi | ụda égbè | |
| handgun | مسدس | pistolet | | | |
| handguns | المسدسات | armes de poing | | égbè mkpụmkpụ | |
| hostiles | معادية | | | | |
| hostilities | الأعمال العدائية | hostilités | tashin | | igboro |
| hostility | عداء | hostilité | rashin jituwa | iro | igbogunti |
| infantry | المشاة | infanterie | dakaru | bipu | ẹlẹṣẹ |
| ied | العبوات الناسفة | | bama-bamai | | |
| ieds | العبوات الناسفة | | bamai | | |
| injure | جرح | blesser | cuta | emerụ | ipalara |
| injured | جرح | blessé | ji rauni | merụrụ ahụ | farapa |
| injures | اصابات | blesse | | emerụ | |
| injuries | إصابات | blessures | raunin da ya faru | unan | nosi |
| injuring | إصابة | blessant | jikkata | merụọ | |
| injury | ضرر | blessure | rauni | mmerụ | ipalara |
| insurgencies | التمرد | insurrections | hare haren | | |
| insurgency | تمرد | insurrection | tayar da kayar baya | | |
| insurgent | متمرد | insurgé | hare | | |
| insurgents | المتمردين | insurgés | maharan | | |
| invade | غزو | envahir | mamaye | wakporo | gbogun |
| invaded | غزت | envahi | mamaye | wakporo | yabo |
| invader | غاز | envahisseur | mai mamaye | onye mbusoagha | |
| invaders | الغزاة | envahisseurs | | mwakpo | |
| invades | يغزو | envahit | ta mamaye | awakpoo | |
| invading | الغازية | envahisseur | | na-awakwasị | |
| invasion | غزو | | mamayewa | mbuso agha | ayabo |
| invasions | الغزوات | | mamayar | mwakpo | |
| kill | قتل | tuer | kashe | igbu | pa |
| killed | قتل | tué | kashe | gburu | pa |
| killer | القاتل | tueur | kisa | egbu egbu | apani |
| killers | القتلة | tueurs | kisan | | aporó |
| killing | قتل | meurtre | kashe | okowot | pipa |
| killings | القتل | tueries | kashe-kashe | | |
| kills | يقتل | tue | kashe | egbu | pa |
| land mine | لغم أرضي | mine terrestre | | ala m | ilẹ mi |
| land mines | الألغام الأرضية | les mines terrestres | ƙasar mahakai | ogbunigwe | ilẹ maini |
| landmine | الألغام الأرضية | les mines terrestres | | | |
| landmines | الألغام الأرضية | les mines terrestres | nakiyoyin da | | lese |
| machinegun | رشاش | mitraillette | | | |
| machineguns | الرشاشة | mitrailleuses | | | |
| maim | جرح | mutiler | | | maimu |
| maimed | شوهوا | estropié | | nkwarụ | àbùkù |
| maiming | التشويه | mutilation | | | sofo ti |
| maims | يشوه | mutile | | | |

## Table A1 (cont.) Nigerian Multilingual Dictionary of "armed conflict"

| English | Arabic | French | Hausa | Igbo | Yoruba |
|---|---|---|---|---|---|
| marines | المارينز | | sojin rundunar jiragen ruwa | | marini |
| massacre | مذبحة | | kisan kiyashin | mgbuchapụ | ipakupa |
| massacred | ذبح | massacrés | karkashe | | |
| massacres | المجازر | | kisan kiyashi | | |
| massacring | ذبح | massacrant | | | |
| militarize | أضفى الصفة العسكرية | militariser | sojoji | | |
| militarized | عسكرتها | militarisée | yan bindiga a | agha | |
| militarizing | عسكرة | militarisation | | | |
| military | عسكري | militaire | soja | agha | ologun |
| missile | صاروخ | | makami mai linzami | agha | misaili |
| missiles | صواريخ | | jifa | akụ ụta | |
| mortar | هاون | mortier | turmi | ngwa agha | amọ |
| mortars | قذائف الهاون | mortiers | | | |
| murder | قتل | assassiner | kisankai | igbu ọchụ | iku |
| murdered | قتل | assassiné | kashe | gburu | paniyan |
| murderer | قاتل | assassin | kisan kai | na-egbu ọchụ | apànìyàn |
| murderers | القتلة | meurtriers | kisankai | na-egbu ọchụ | apànìyàn |
| murdering | اغتيال | meurtre | kashe | -egbu ọchụ, | |
| murderous | القاتل | meurtrier | suka kai | igbu ọchụ | ipaniyan |
| murderously | مهلك | | | | |
| murders | القتل | meurtres | kisan kai | ikwa | |
| mutilate | بتر | mutiler | daddatsa gawa | ebepụ | |
| mutilated | المشوهة | mutilé | | | |
| mutilates | يمزق | mutile | | | |
| mutilating | تشويه | mutilant | jikin | | |
| naval | بحري | | sojan ruwa | | to ọkọ |
| navies | القوات البحرية | marines | | | |
| navy | سلاح البحرية | | sojojin ruwa | agha mmiri | ọgagun |
| ordinance | مرسوم | ordonnance | farilla | ukpuru | ìlana |
| ordinances | المراسيم | ordonnances | hukuncen | | idajọ |
| pistol | مسدس | pistolet | bindiga | egbe | ibon |
| pistols | مسدسات | pistolets | | obere égbè | |
| platoon | مفرزة | | mutanena su ka | | |
| platoons | فصائل | pelotons | | | |
| raid | غارة | | hari | wakporo | igbogun ti |
| raided | داهمت | perquisitionné | kai hari | wabara | |
| raiding | الإغارة | raids | hari | | ẹgbẹ ogun |
| raids | الغارات | | hare-hare | | |
| rape | اغتصاب | viol | fyade | n'ike | ifipabanilopo |
| raped | اغتصاب | violé | fyade | n'ike | lopọ ti |
| rapes | الاغتصاب | viols | | | ifipabanilopo |
| raping | اغتصاب | viol | fyade | | |
| rapist | مغتصب | violeur | yarsu fyaden | | |
| rapists | المغتصبين | violeurs | | | afipabanilo |
| rebel | متمرد | rebelle | yan tawayen | enupu isi | ṣọtẹ |
| rebelled | تمرد | rebellés | tawaye | nupụrụ isi | ṣọtẹ |
| rebelling | تمرد | rebeller | tawaye | enupụ isi | ti ṣọtẹ |
| rebellion | تمرد | rébellion | tawayen | nnupụisi | iṣọtẹ |
| rebellions | التمرد | rébellions | tawayen | nupụ isi | |
| rebellious | متمرد | rebelle | | enupụ isi | ọlọtẹ |
| rebels | الثوار | rebelles | yan tawayen | nnupụisi | olote |
| revolt | ثورة | révolte | yi tawaye | nnupụisi | sote |
| revolts | الثورات | révoltes | yin tawaye | nnupụisi | |
| revolver | مسدس | | | égbè | |
| revolvers | المسدسات | | | | |
| rifle | بندقية | fusil | bindiga | égbè | ibọn |

## Table A1 (cont.) Nigerian Multilingual Dictionary of "armed conflict"

| English | Arabic | French | Hausa | Igbo | Yoruba |
|---|---|---|---|---|---|
| rifleman | حامل بندقية | fusilier | | | |
| riflemen | الرماه | tirailleurs | | | |
| rifles | بنادق | fusils | bindigogi | | awọn iru ibọn kan |
| riot | شغب | émeute | | ntịme | ìṣọtẹ na |
| rioted | قاموا بأعمال شغب | se sont révoltés | | | |
| rioter | متظاهر | émeutier | | | |
| rioters | مثيري الشغب | émeutiers | masu zanga-zangar | | |
| rioting | أعمال شغب | émeutes | | | |
| riots | أعمال الشغب | émeutes | tarzoma | | |
| rocket | صاروخ | fusée | roka | rọketi | |
| rocketfire | نيران الصواريخ | | | | |
| rocketlauncher | قاذفة الصواريخ | lance-roquettes | | | |
| rocketlaunchers | | | | | |
| rockets | صواريخ | roquettes | roka | tammy | |
| security | أمن | sécurité | tsaro | nche | aabo |
| shelled | مقشر | décortiquées | | | |
| shelling | قصف | bombardement | wuta ya janyo | | |
| shotgun | بندقية الصيد | fusil de chasse | | | ibọn |
| shotguns | البنادق | fusils de chasse | | | |
| slaughter | ذبح | abattage | kashe | akwụ | |
| slaughtered | ذبح | abattus | yanka | gbuo | pa |
| slaughtering | ذبح | abattage | yanka | ogbugbu | ẹran |
| slaughters | مجازر | tueries | yanka | | |
| small arms | الأسلحة الصغيرة | petites armes | kananan makamai | obere ogwe aka | kekere apá |
| sniper | قناص | tireur isolé | maharbi | | |
| snipers | القناصة | | makasa | | orukoô |
| soldier | جندي | soldat | soja | agha | jagunjagun |
| soldiers | جنود | soldats | sojoji | agha | ogun |
| stabbed | طعن | poignardé | sukan | adụ | leyiti |
| stabbing | طعن | élancement | caka | ịma | nibi |
| strike | إضراب | grève | yajin | iku | idasesile |
| strikes | الضربات | grèves | buga | etiwapụ | dasofo |
| striking | مضرب عن العمل | frappant | daukan hankali | pụtara ìhè | idaṣẹ |
| struck | ضرب | frappé | bugi | gburu | lù |
| suicidal | الانتحار | suicidaire | | igbu onwe | |
| suicide | انتحار | | kashe kansa | igbu onwe | ara |
| terror | الإرهاب | terreur | tsõro | oké ụjọ | eruolorun |
| terrorise | إرهاب | terroriser | ta'ada | menyeujo | |
| terrorised | روعت | terrorisé | | | |
| terrorises | يرهب | terrorise | | | |
| terrorising | إرهاب | terrorisant | tayar da hankalin | | |
| terrorism | إرهاب | terrorisme | ta'addanci | iyi ọha egwu | ipanilaya |
| terrorist | إرهابي | terroriste | 'yan ta'adda | eyi ọha egwu | apanilaya |
| terrorists | الإرهابيين | terroristes | 'yan ta'adda | eyi ọha egwu | onijagidijagan |
| terrorize | إرهاب | terroriser | ta'ada | menyeujo | |
| terrorized | روعت | terrorisé | | | |
| terrorizes | ترعب | terrorise | barazana, | | |
| terrorizing | إرهاب | terrorisant | tayar da hankalin | | |
| threat | التهديد | menace | barazana | iyi egwu | irokeke |
| threaten | هدد | menacer | barazana | ize | deruba |
| threatened | مهددة | menacés | barazana | egwu | ewu |
| threatening | مهدد | menaçant | barazana | na-eyi egwu | ihal |
| threateningly | مهددا | menaçant | | egwu | |
| threatens | يهدد | menace | barazana | egwu | irokeke |
| threats | التهديدات | menaces | barazana | egwu | irokeke |

## Table A1 (cont.) Nigerian Multilingual Dictionary of "armed conflict"

| English | Arabic | French | Hausa | Igbo | Yoruba |
|---|---|---|---|---|---|
| troop | قوات | troupe | ƙungiya | | |
| troops | القوات | troupes | dakarun | agha | enia |
| victim | ضحية | victime | wanda aka azabtar | aja | njiya |
| victims | ضحايا | victimes | wadanda ke fama | metụtara | olufaragba |
| violence | عنف | | tashin hankali | ime ihe ike | iwa-ipa |
| violent | عنيف | | | eme ihe ike | iwa |
| violently | بعنف | violemment | | ike | |
| war | حرب | guerre | yaki | agha | ogun |
| warfare | حرب | guerre | yaki | agha | yce |
| warfighter | المحاربون | combattant | | | |
| warfighters | قوات مقاتلة | combattants | | | |
| warmonger | مثير الحرب | belliciste | | | |
| warmongers | دعاة الحرب | bellicistes | | | |
| warplane | طائرة حربية | avion de combat | | | |
| warplanes | طائرات حربية | avions de combat | jirage | | |
| warred | حارب | guerroyé | yaki | agha | n gbogun ti |
| warring | مقاتل | en guerre | yaƙe | ebu agha | |
| warrior | محارب | guerrier | | | jagunjagun |
| warriors | المحاربين | guerriers | | dike | |
| wars | الحروب | guerres | yaƙe-yaƙe | agha | ogun |
| warship | سفينة حربية | navire de guerre | | | |
| warships | سفن حربية | navires de guerre | | | |
| wartorn | مزقته الحرب | | | | |
| weapon | سلاح | arme | makami | ngwá agha | multani |
| weaponry | أسلحة | armes | makamai | ngwá agha | |
| weapons | أسلحة | armes | makamai | ngwá agha | ohun ija |
| wound | جرح | blessure | rauni | ọnya | egbo |
| wounded | جريح | blessés | rauni | merụrụ | ti o gbọgbẹ |
| wounding | جرح | blessant | ji masa rauni | | |
| wounds | الجروح | plaies | raunuka | ọnyá | ọgbẹ |